Mixed causal-noncausal models

Valorization

"Strive not to be a success, but rather to be of value."
-Albert Einstein (1879-1955)

Knowledge valorization refers to the utilization of scientific knowledge in practice. While reading a scientific work, one may ask questions like: *"what is the societal relevance?"* and *"what is its contribution to real life phenomena?"*. In this addendum, I outline the knowledge valorization of modelling time series processes by means of mixed causal-noncausal autoregressive models, which is the main topic of this dissertation. In particular, I discuss the social and economic relevance of the topic and the respective results, potential target groups, translated services, processes and activities, as well as the innovativeness and implementability of the research.

As discussed in the Introduction, noncausal autoregressive models are common in various scientific fields (e.g., physics and astronomy) but relatively novel in the field of econom(etr)ics. In this dissertation, the noncausal model as well as a combination of causal and noncausal models (i.e., the mixed causal-noncausal model) is applied to various macroeconomic and financial time series, often leading to a better in-sample fit than conventional autoregressive models. This is due to the fact that these models can capture certain nonlinear dynamics that previously could only be picked up by very complex models. In other words, mixed causal-noncausal models are able to replicate features such as speculative bubbles and asymmetric cycles that are often present in economic data. Especially over the last years, one can find various time series displaying patterns that resemble a bubble (e.g., dot-com bubble, American housing crisis, bitcoin and property bubbles in various countries) and thus it is fair to argue that there is a need for relatively simple models that can accommodate such features. To that end, theoretical and empirical research on these models can improve the understanding of certain economic and financial processes. From a very general point of view, anyone interested in explaining these types of data series can benefit from a thorough study on these models. If statistical agencies and policy makers decide to adopt the mixed causal-noncausal autoregressive model, it can be argued that its influence is extended to a much larger crowd, who benefits either directly or indirectly from the research in this field.

The answer to the question whether the mixed causal-noncausal model is going to be broadly adopted in the future, is not known at this point in time. Allowing for noncausality seems to be a rather natural way to extend the Box-Jenkins methodology, which has been one of the most common approaches in time series model selection since the seventies. It extends the existing procedure in the sense that the set of possible dynamic models that can be chosen increases greatly.

Hence, it offers practitioners more flexibility in modelling time series of interest. In case this extension of the Box-Jenkins approach becomes standard, research in this field can constitute to new topics taught to students in the field of econometric theory.

In the current literature, one can find many theoretical results on the mixed causal-noncausal autoregressive model. In particular, Rosenblatt (2000) provides an extensive investigation of stationary autoregressive and moving average linear sequences and random fields in the non-Gaussian context. This monograph has inspired researchers to introduce noncausality in the world of econom(etr)ics. Since non-Gaussianity of the process is required to distinguish between purely causal, noncausal and mixed causal-noncausal models, it has been an important aspect in the literature. More specifically, one can distinguish between two different streams: the Gaussianity assumption of the error distribution is abandoned and rather assumed to be (*i*) a nonstandardized Student's t-distribution and the model is estimated by maximum likelihood or (*ii*) an α-stable distribution (or the weaker assumption that the law of the errors belongs to the domain of attraction of a stable distribution) and the standard least-squares method is adhered to. Both approaches have their merits but also have clear disadvantages. Most notably, the first case requires a (potentially misspecified) parametric assumption on the error distribution. In the second case, the process is assumed to have (at least) infinite variance, which complicates the analysis (as it heavily affects asymptotic results) and might be an unrealistic assumption. This only illustrates that more theoretical research is necessary to make clever decisions in modelling mixed causal-noncausal processes.

This dissertation aims to offer a contribution to this theoretical study but mostly focuses on the empirical side of it. In contrast to the various papers that establish the theoretical foundations of the mixed causal-noncausal model, the number of applied papers is very limited. This dissertation fills this gap in the literature in three different ways. Firstly, the finite sample performance of different estimators is studied and closed-form solutions to compute standard errors are provided (Chapter 2 and 4). Whereas asymptotic results are very important in the field of time series econometrics, practitioners often experience different types of problems in empirical work. These chapters address those issues and provide a clear guidance on how to swiftly implement mixed causal-noncausal models (potentially including exogenous regressors). Secondly, the mixed causal-noncausal model is studied in relation to two very important econometric concepts: seasonal adjustment and common features (Chapter 3 and 5). In the first chapter, the effect of seasonal adjustment methods on the selection of mixed causal-noncausal models is considered. Seasonal adjustment of time series is a tedious procedure that might introduce unwanted side-effects. This can lead to a wrong assessment of the importance of forward- and backward-looking behavior of variables of interest, which can have important consequences for e.g. forecasting and policy implementation. The second chapter investigates whether more common features between series can be discovered when one allows for noncausality. The detection of common features is important as it can unravel links between different variables, which is of interest for various reasons (e.g., policy measures, spillover effects, forecasting). Thirdly, routines are developed which make it easy for practitioners to simulate, estimate and select mixed causal-noncausal models (Chapter 6). More specifically, an R package is freely available online which attempts to reduce the gap between theoretical and applied results in this field considerably.

Despite their immediate interest for macroeconomic and financial researchers, the contributions presented in this thesis are not restricted to that particular field. The R package can be used in various studies which intend to fit mixed causal-noncausal models to their data of interest (e.g., physics and astronomy mentioned before). Moreover, as researchers only have a limited amount of data available, the finite sample results can also prove to be useful for practitioners in several fields. Even the results for the effect of seasonal adjustment on model selection of mixed causal-noncausal models can be generalized beyond the exercise of seasonal adjustment. The extensive simulation study of Chapter 3 shows how linear filters, which are often applied to data (e.g., taking average of three months to compute a quarterly observation), affect the choice for the final model. In addition, the tests proposed to detect common features do not specify a certain type of commonality. Whereas this dissertation focuses on common features in economic data, there is no reason to expect that the tests fail to identify any other types of common features.

Most importantly, it seems that mixed causal-noncausal models offer a relatively simple alternative to highly nonlinear and complex models. In general, it appears that researchers face the following trade-off when they want to model processes with complex dynamics: either one favors a complex (nonlinear) model with (simple) Gaussian disturbances or one chooses a simple (linear) model with complex (e.g. infinite variance) disturbances. So far, the focus in economics was mostly on the former option. The mixed causal-noncausal model now provides the latter option and seems to be rather successful in modelling economic processes. However, there are still many avenues for future research. In particular, the non-nestedness of mixed causal-noncausal models introduces severe complications for model selection. Additionally, standard tests in time series econometrics (e.g., unit root tests) are (or might be) no longer applicable in the presence of noncausality and thus have to be re-examined, which hopefully leads to the development of an appropriate set of tools. In terms of the model, one could think of various interesting extensions, for example generalized autoregressive conditional heteroskedasticy (GARCH) and vector error correction (VECM) models. For additional proposed future research, I would like to refer the reader to the conclusions of the respective chapters. I hope that the methods considered in this dissertation are also employed outside of the academic world. As a last remark, I want to point out an important part of valorization that is often overlooked: writing this thesis has made me a better researcher and teacher, which - hopefully - also has a significant impact on society.